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AUTOMATED SCHEDULING METHOD FOR REDUCING SPATIAL-TEMPORAL CONFLICT SAFETY RISKS, USING ML AND BIM

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SUMMARY*: Construction sites face inherent risks from overlapping activities in confined spaces and require advanced solutions to manage spatial-temporal conflicts. Surpassing previously developed static BIM tools, this study introduces an automated approach that revolutionizes job site safety planning by dynamically assessing conflict risks between evolving workspaces. The method integrates empirical workspace geometry with machine learning—using Support Vector Machine regression to predict worker presence—and BIM-driven dynamic conflict analysis, which reflects real-time changes in workspace sizes and team movements. By generating safety score matrices through pairwise risk assessments, it quantifies conflict types (physical impacts, proximity risks, workflow disruptions) and enables real-time scenario comparisons via Python-based evaluation. Adjustable parameters allow customization for team sizes, workspace allocations, and pandemic-specific adaptations such as social distancing. Case studies show that the system effectively identifies high-risk periods, compares different work sequences, and makes schedules without sacrificing productivity. Unlike earlier clash detection methods that only compared static models, this framework provides actionable safety metrics to proactively respond to conflict risks. Designed for scalability, the presented method manages computational demands in complex projects. This advancement represents a paradigm shift in construction safety, blending predictive analytics with practical adaptability to protect workers and streamline operations.*

KEYWORDS*: Safety Management, Building Information Modeling, Spatial-Temporal Conflicts, Workspace Modeling, Workspace Visualization.*

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1. INTRODUCTION

Despite technological advances in Occupational Health and Safety (OHS), the construction industry has remained a high-risk industry with high injury and fatality rates (Tixier et al., 2017; Ghodrati et al., 2018; Alkaissy et al., 2020). As a construction project progresses, constant changes in the physical environment and the turnover of crews and machinery result in different risk levels (Rozenfeld et al., 2009). Construction workers are exposed to hazards from the technology (including tools and machinery necessary to perform the task), physical and environmental conditions, and surrounding activities (Mitropoulos et al., 2005). Safety hazards of different construction activities and the role of the environment have been previously studied (Benjaoran & Bhokha, 2010; Esmaeili et al., 2015; Zhang et al., 2015a; Tixier et al., 2017; Choe & Leite, 2017b). This paper focuses solely on detecting and analyzing hazards that stem from the execution of simultaneous activities.

Spatial-temporal conflicts occur when the allocated workspace of an activity interferes with other simultaneous activities. Task overlaps in construction projects are prevalent due to the time pressure, and multiple concurrent tasks competing for a limited workspace (Zhang et al., 2015b). Securing work safety and productivity is difficult in the presence of workspace interference (Igwe et al., 2020; Moon et al., 2014b). Multiple studies tried to address the spatial-temporal conflicts by providing frameworks to detect, analyze and reduce the collision among workspaces in construction projects. More recently, BIM has been integrated into safety planning and workspace management due to its ability to visualize workspaces, conduct safety rule-checking algorithms, and analyze and resolve workspace conflicts. BIM facilitates sharing of sites' safety-related data and supports collaboration (Martínez-Aires et al., 2018).

The BIM-based method presented in this paper consists of five main components; construction workspaces 2D graph, BIM model, Support Vector Machine regression, safety score matrices, and scenario evaluation code. The presented method classifies and generates activity-specific workspaces based on empirical data first. Subsequently, construction workspaces 2D graph, SVM regression, and BIM model are used to conduct pair-wise conflict detection and analysis. The outputs of this process are safety score matrices regarding conflicts of different activities such as post-installation/post-installation or post-installation/blockwork, etc. The Phyton code uses the matrices to carry out scenario evaluation. The final outputs of this method are the safety scores for each scenario (at each time unit and cumulatively). The calculated safety scores could be used as criteria to compare different scenarios, identify high-risk periods, and warn safety managers to proactively respond to risks or to alert contractors to adjust the work sequences.

Support Vector Machine Regression (SVM) is a non-probabilistic binary linear classifier that was used to anticipate the number of blockwork laborers' visits to each workspace module based on training examples. Although other machine learning algorithms such as Neural Network and Random Forests could be used for this purpose, SVM regression with a radial basis function kernel (RBF) was used to map the input into high-dimensional feature spaces, making them more separable with reasonable computational complexity. Moreover, hyperparameters such as the regularization parameter (C) and kernel parameters were carefully tuned to avoid overfitting and underfitting (mean squared error of 0.9589 in all data).

Blockwork and post-installation activities in a healthcare facility construction project were used to validate the method. The activity-specific information about these activities, including the required workspace and the evolving workspace geometries (dynamic evolution) of the allocated workspaces, was missing in the literature. This gap was filled by collecting data through field observation, manual data entry, sample simulation and analysis in Grasshopper®, and processing the data through Support Vector Machine (SVM) regression (Kluyver et al., 2016).

Compared to traditional safety management practices, which relied on a safety expert to identify hazards based on static information (e.g., two-dimensional drawings and paper regulations), the method presented in this paper takes the dynamic nature of the construction phase into consideration and addresses site-specific information.

This method uses parametrically generated occupancy grids based on empirical data to represent workspace usage over time and conduct conflict detection and analysis. The approach is superior to the methods that used variants of the Bounding Box concept (e.g., Bounding Spheres (BS), Axis-Aligned Bounding Box (AABB), and Oriented Bounding Boxes (OBB)) (Chavada et al., 2012; Moon et al., 2014a; Kim & Teizer, 2014; Kim et al., 2016; Mirzaei et al., 2018; Dashti et al., 2021; Wang et al., 2019). It is because by considering workspace usage during the construction time of each activity, unrealistic conflict detection is avoided. Also, compared to expert opinion approaches and other non-empirical methods subject to cognitive bias, quantifying conflict risks could be done more accurately. Furthermore, although some commercial 3D modeling systems such as Autodesk® Navisworks® and SYNCHRO Pro® could detect collisions between design elements and workspaces, these models cannot quantify the risk of conflict. In this novel method, conflict detection and analysis are carried out by automatically cross-checking the work sequence of different activities using the Python code, discussed in section 3.7.

2. LITERATURE REVIEW

Although digital technologies have entered the construction industry for several decades, making use of them in occupational health and safety (H&S) has been lower compared to other construction fields (Cortés-Pérez et al., 2020). In recent years, researchers have started applying BIM (i.e., Building Information Modeling) to enhance safety planning and site monitoring. However, tailoring BIM to suit construction management tasks such as workspace planning has remained a challenge (Igwe et al., 2020).

The following subsections detail the main highlights from different research studies on BIM-based safety management, safety risk analysis, and workspace management.

2.1 BIM-Based Safety Management

Traditional safety management practices have been argued to be time-consuming, done separately from the design and planning phase, highly dependent on traditional resources such as two-dimensional drawings and paper regulations, inconsiderate of the dynamic nature of the construction phase, and reliant on a safety expert to identify hazards and determine safety equipment based on experience (Zhang et al., 2015a; Choe & Leite, 2017b; Guo et al., 2021). Reliance on static information and tacit knowledge in traditional safety planning approaches results in not addressing site-specific dynamic information, temporal (e.g., when and who will be exposed to potential hazards), and spatial (e.g., location of dangerous zones) information (Choe and Leite, 2017b). Due to the Inefficiency of traditional safety management in identifying and analyzing hazards, approaches based on information technology such as building information modeling (BIM), geographic information system (GIS) (Bansal, 2011), augmented reality (AR) and virtual reality (VR), and Sensing and Warning Technologies have been considered in recent years.

As the most flourishing technology in the construction industry, BIM has the potential to contribute to safety management e.g. through scheduling, clash detection, construction progress tracking, design consistency and visualization, data integration, cost estimations, implementation of lean construction, or improved team member collaboration, etc. (Martínez-Aires et al., 2018). Since an optimal way to improve safety performance is thorough accident prevention (Alkaissy et al., 2020), researchers have applied BIM to identify potential safety hazards through 1-visualization or 2-automatic rule-based algorithms and adopting corresponding prevention methods. Visual technologies such as BIM could be used to facilitate identifying job hazard areas (JHAs) during safety meetings and aid safety training (Zaman et al. 2024). Although taking advantage of BIM, this approach to safety risk identification is still an experience-dependent manual process. Benjaoran and Bhokha (2010) integrated a 4D CAD model (Flores and Mourgues, 2024) and a rule-based system to automate the working-at-height hazard identification process and suggest proper safety measures, including safety activities or requirements. A similar approach was adopted by Zhang et al. (2015a) to identify the risks of fall from height at the early stages of planning and raise workers' safety awareness by using three-dimensional visualization of potential hazards. Kim et al. (2016) focused on scaffolding construction and used rule-checking algorithms to identify and prevent hazards arising from the sequence of activities and temporary structures.

2.2 Safety Risk Analysis

Most safety risk studies decompose construction processes into smaller parts to overcome the technological and organizational complexity of construction process (Tixier et al., 2017). This decomposition could assist researchers in analyzing safety for specific tasks or activities (Benjaoran & Bhokha, 2010), for different trades or occupations (Choe & Leite, 2017b), based on model elements (Cortés-Pérez et al., 2020), or for specific hazards such as fall from height (Zhang et al., 2015a).

The main limitation of the above-stated segmented approaches is that identifying all safety risks of each trade, activity or task is impractical, especially in large-scale and sophisticated projects (Tixier et al., 2017; Ghodrati et al., 2018). To address this limitation, context-free measurable and predictable attributes of the work environment could be identified through content analysis of safety reports to assess safety risks for a worker, group, activity, profession, or site as a whole. This approach was first adopted by Esmaeili et al. (2015) and further developed by Tixier et al. (2017) (a genetic-inspired attribute-based model). However, attribute-based assessment overlooks the fact that safety attributes for different trades may have different probabilities and severities. The risk score for each attribute is considered to be constant regardless of different professions (Choe & Leite, 2017a).

Current risk quantification methods either use historical data or, more commonly, expert opinion and other non-empirical methods subjected to cognitive bias to assess safety hazards (Esmaeili et al., 2015; Tixier et al., 2017). For instance, Jannadi and Almishari (2003) developed a user-friendly computer model for assessing safety risks based on expert opinion values on probability, severity, and exposure. In a similar approach, Rozenfeld et al. (2010) presented a time and space-dependent model to calculate the risk of each loss of control event. Their model considers the impact of teams on each other, but no human factors, such as Myopia or illness, have been taken into account. Cortés-Pérez et al. (2020) proposed a BIM-based methodology in which the importance of the hazards related to each component in the 3D model is determined by manually entering the severity and probability of safety risks in the Dynamo plugin. Hallowell and Gambatese (2009) used the Delphi method to quantify the severity and frequency of safety risks and determine the degree of exposure through observation to minimize cognitive biases. On the other hand, relying on statistical data, researchers use data from historical events provided by the National databases to assess safety risks. Baradan and Usmen (2006) used historical data to quantify the risk of injury and death of construction-related occupations using two dimensions: probability and intensity. Esmaeili et al. (2015) conducted a content analysis of struck-by incident reports to assess safety risks. In their approach, the location and time of activities and their impact on each other have been considered. To consider the unique nature of each activity, Choe and Leite (2017a) examined the data on fatality and days-away injuries presented by the US Bureau of Labor Statistics and obtained the relative safety score of 19 private sector occupations in the construction industry. Although using previous accident reports to assess safety risks can provide a more reliable estimate, this approach requires a reliable technical database to review the data effectively. It should also be noted that incident reports provided by relevant organizations and departments usually only include high-severity incidents. Still, low-severity incidents and near-miss events are not reported.

2.3 Workspace Management

The terminology 'Workspace management' could be defined as the process of workspace generation, allocation, conflict detection, and conflict resolution at any time during a construction project (Chavada et al., 2012). In recent years, construction workspace management has become a matter of concern in research and practice due to the necessity to improve productivity and safety by reducing spatiotemporal clashes between activities (Igwe et al., 2020).

Traditional workspace planning methods do not consider the spatial feature of each activity (Choi et al., 2014), do not appear to have an adequate visual representation, and are limited in terms of workspace–time conflicts analysis. Furthermore, using conventional planning methods to manage workspace is particularly challenging when it comes to micro-scheduling of short-duration activities requiring the use of heavy construction equipment due to the dynamic nature of construction activities (Igwe et al., 2020).

The existing literature could be divided into two categories in terms of determining the required workspace. The first category of articles specifies the required workspace for performing the activities per person regardless of the type of activity, the conditions of the work, and the construction method. For example, Chua et al. (2010) stated that each worker needs 0.6 m3 of space. The second category considers the type of activity or construction method to determine the required workspace. The required workspace could be determined by measuring through a three-dimensional model, estimation based on physical properties, estimation of crew productivity, construction manager's experience, observation, and historical data (Thabet & Beliveau, 1994; Riley & Sanvido, 1997; Guo, 2002; Moon et al., 2014a; Choi, et al. 2014; Zhang et al., 2015b; Kim et al., 2016; Dashti et al. 2021).

Wang et al. (2019) categorized current workspace modeling studies by two methods: solid geometry-based or cell-based. The solid-based method refers to an approach that utilizes one or more geometry solids to represent the space requirements. Chavada et al. (2012); Moon et al. (2014a); Kim & Teizer (2014); Kim et al. (2016); Mirzaei et al. (2018); Wang et al. (2019); Dashti et al. (2021) adopted the solid geometry-based method and used bounding boxes and variants of it to generate the required workspace. The solid-base method could automatically generate a workspace based on the model elements (Akinci et al., 2002), digital construction methods (Choi et al., 2014), or historical tracking data (Zhang et al. 2015b), and easily detect and analyze workspace clashes since workspaces are geometric elements. However, to model irregularly moving objects (e.g., a truck) the cell-based method must be adopted, which uses a series of cells (grids and nodes) to represent space usage (Wang et al., 2019). The cell-based approach has been developed to simulate resource movement and plan floor-level construction material layout (Park et al., 2012), for near real-time simulation of earthwork equipment workspaces, to find the shortest travel path for mobile cranes, and to detect transport Path Obstruction (Wang et al., 2019).

Instead of imposing parametric models on data gathered from complex systems with unknown mechanisms (e.g., workspace usage during construction activities), algorithmic models such as neural networks, classification trees, and Support Vector Machines (SVMs) may obtain higher accuracy and be used for data classification and pattern recognition. Although other machine learning algorithms could be used to model linear and non-linear datasets, SVMs are highly contingent in the construction domain and have been used to predict deviation from the project's objectives, project control, dispute resolution, cost estimation, and performance prediction (Shafaat et al., 2022; Golazad et al., 2024).

Hazard could arise from spatial and temporal relationships between building elements, materials, temporary equipment and tools, operations, and human workspace (Guo et al., 2021). Akinci et al. (2002) define workspace conflicts as conditions when the space requirements for an activity interfere with one another or with work in place. As surrounding simultaneous activity carried out by other workers nearby could expose workers on construction sites to hazards (Mitropoulos et al., 2005; Moon et al., 2014b), detecting, preventing, and resolving any spatial-temporal conflicts is of much significance. Riley & Sanvido (1997) developed a graphical manual space planning method that considers activities' sequences and identifies potential spatial conflicts. The methodology presented by Guo (2002) identifies spatial interactions by marking the required workspaces on two-dimensional maps produced in the AutoCAD software. Visualization technologies (e.g., BIM, 4D CAD, virtual prototyping, virtual reality, and augmented reality) have facilitated the detection and analysis of spatiotemporal clashes. Akinci et al., (2002) used 4D CAD to manually generate temporary structures and automatically detect spatial conflicts between them. In order to automatically detect spatial-temporal clashes, collision detection algorithms have been used to determine conflicts among site entities and time-dependent structure components, temporary structures, and workspaces (Moon et al., 2014a; Kim et al., 2016). Correspondingly, Choi et al. (2014) proposed a framework that used a spatial clash-detection algorithm to detect workspace conflicts. However, their approach is more accurate in terms of representing workspace utilization over time by breaking down each activity into several sub-activities passing through part of the required space during the entire activity duration. Dashti et al. (2021) developed a software application as an add-on for Autodesk® Navisworks® Manage to generate workspaces as variants of the bounding box and to automatically compute the collision percentage by dividing the number of collided cuboids into the total number of cuboids for each workspace. In their approach, some if-then rules are defined based on site engineers' opinions and coded to evaluate the detected conflicts. To represent workspace usage over time, the BIM-based approach developed by Zhang et al. (2015b) computes accurate workspace occupation parameters based on historical data to represent workspace usage over time and detects potential workspace conflicts among work crews or between material lifting equipment. Taking conflict detection a step further, Moon et al. (2014b) suggested an optimized algorithm based on a location-constraint genetic algorithm accompanied by a 4D CAD system to minimize workspace interference.

3. PROPOSED METHOD

After reviewing the existing literature regarding workspace management, it was revealed that although workspaces of construction activities have evolving geometries during the construction process, the approaches using Bounding Box and variants of it to represent workspaces are unable to capture the dynamic evolution of workspaces (Igwe et al., 2020). The majority of previous studies, including Thabet & Beliveau, 1994, Akinci et al., 2002; Guo, 2002; Chavada et al. 2012; Moon et al., 2014a; Dashti et al., 2021, assumed that the workers occupy the workspace allocated to each activity for the entire duration of the activity. This notion neglects the fact that the required labor occupies only a portion of the activity's workspace during each time interval and may result in unrealistic conflict detection (Mirzaei et al., 2018). Furthermore, commercially available 4D Virtual Construction Scheduling and Simulation software such as Autodesk® Navisworks® and Synchro Pro, albeit offering clash detection tools, are limited to identifying and representing conflicts between workspaces and do not quantify the risk of conflict between them. Therefore, a robust method is required to represent workspace usage over time and conduct conflict detection and analysis based on the dynamic nature of construction activities.

The presented BIM-based method considers spatial requirements for construction activities and represents workspace usage based on empirical data. This method, thus, facilitates the spatial-temporal conflict detection and analysis process. It provides the project safety managers with pertinent information regarding whether the planned construction sequence is appropriate and should be executed in terms of the safety impacts of concurrent activities and it could be used during the decision-making process to select the appropriate alternative.

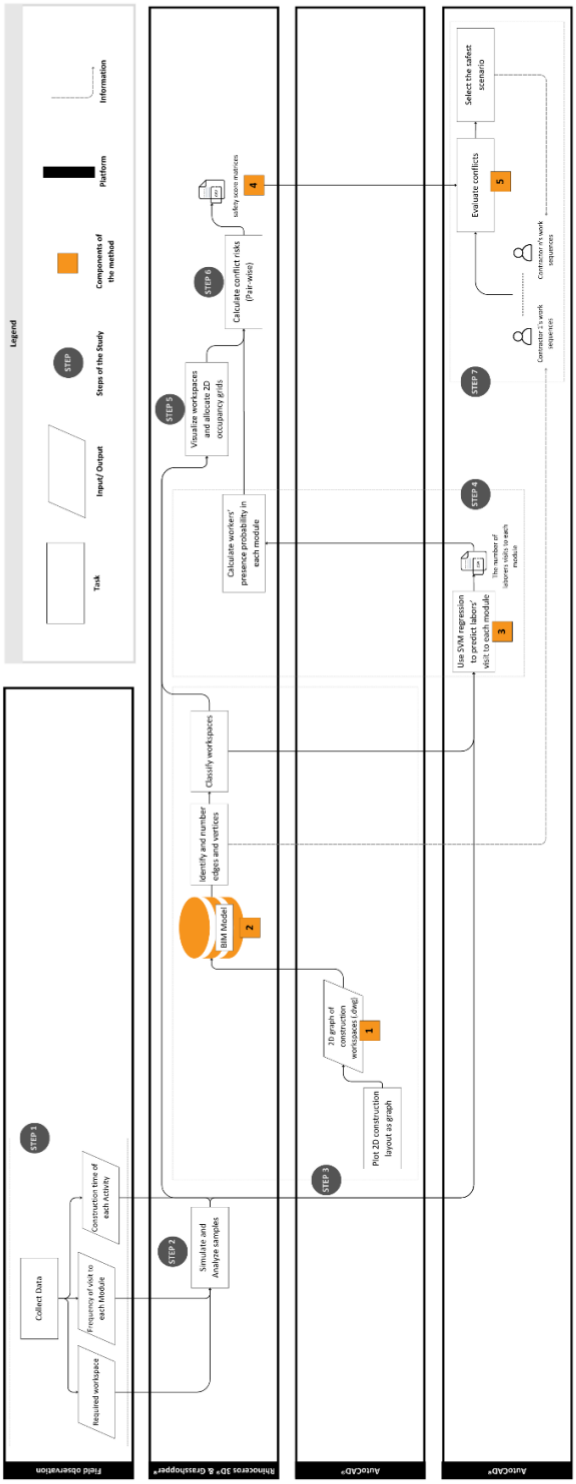


Figure 1: The proposed Method.

The method consists of five main components; construction workspaces 2D graph, BIM Model, Support Vector Machine regression, safety score matrices, and scenario evaluation code in Python. Fig.1 demonstrates the interrelation among the framework's components and illustrates a schematic diagram of the proposed method. The steps of the method will be elaborated in more detail in the following sub-sections.

3.1 Step 1: Field Observations

Blockwork and post-installation activities are common construction tasks that could be executed concurrently. These tasks are inherently linked to each other, as installing the two posts of each wall are precedent for the blockwork activity of that wall (mandatory dependency). As numerous walls could be constructed during each unit of time in a project, the spatial-temporal clashes between blockwork and post-installation activities could inundate workers with safety risks. Thus, these activities were opted for a more detailed study.

Four samples of blockwork (executed by groups of 2 workers) in the project were filmed over four days to obtain information such as the amount of space required by the workers, the frequency of workers' visits to any point of these spaces, and the construction time. Before filming, the construction space in front of each wall was divided into a grid with identical dimensions: 0.5m × 0.5m. Subsequently, these videos were converted into photos (frames) at two-second intervals. Based on these photos, the space required for blockwork activity (details are described in 3.2), the number of visits to each module (details are described in 3.4), and the construction time of each wall were determined. Table 1 depicts the data that was collected from the observed samples of blockwork activity.

To determine the required workspace for post-installation activity (executed by groups of 2 workers) and the construction time of it, three installations were filmed and then observed frame by frame. Since all the posts in the project have the same height and installation method, the execution time and the required workspace were assumed to be constant for all of them. The result showed that the average installation time of each post is 4 hours. However, each post requires a 4-hour lag (two units of time in this study) for welding confirmation before the blockwork activity of the associated wall can begin. This lag was further considered during the determination of tasks' sequence linear arrays in step 7 by writing the value "-1" twice for each lag between post-installation activities in the sequence array of each contractor (further explanation in 3.7).

Table 1: Observed samples of blockwork activity.

	Wall length	Construction time	Number of examined frames
Sample 1	1.9 m	3:15:34	5867
Sample 2	1.9 m	2:40:06	4803
Sample 3	3.2 m	7:04:09	13231
Sample 4	2.9 m	5:21:18	9647
Total		18:21:07	22878
1:51:13		Average construction time of blockwork activity per meter of wall	

The process of extracting activity-specific workspace parameters could also be done automatically using the Global Positioning System (GPS) and novel algorithms (Zhang et al., 2015b). However, this approach is less accurate, inasmuch as data loggers installed inside the equipment cabin or on workers hardhats could be obstructed by other construction resources such as overhead equipment cabins or materials, and workers' head pose orientation continuously change as well as the line-of-sight of the data logger to the sky.

3.2 Step 2: Samples' Simulation and Analysis in BIM Software

To acquire a deeper understanding of the required workspace and the workers' use of the existing workspace before conducting a quantitative study, each observed sample was simulated in the Rhinoceros 3D® software environment using the Grasshopper® plugin. This parametric approach could be adopted using similar BIM modeling applications such as Autodesk® Dynamo.

The workspace in front of each wall (with the length of X) was modeled parametrically, considering it to be a rectangle with a width of 3.5 m and $2 + X + 2 \leq$ length $\leq 3 + X + 3$. Owing to the fact that based on the gathered data through observation, the frequency of blockwork laborers' visits to each module decreases considerably if the distance from the wall increases by 2 meters, and by moving more than 3 meters (from each side of the wall), the frequency of visits practically reaches zero (Fig.2).

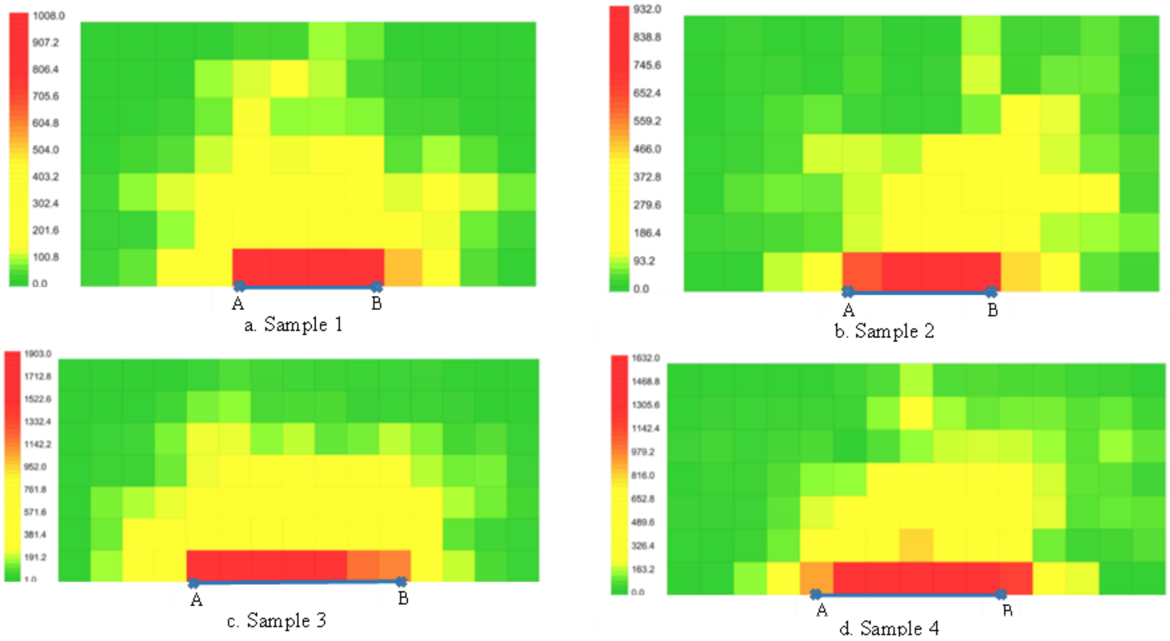


Figure 2: The number of Blockworkers' visits to each module)occupancy grid) in sample 1-4.

Turning to post-installation, the required workspace for each team was simulated as a circle the center of which is the post, and having an adjustable radius based on the field observation data. In this research, the radius was determined to be 2.8 m due to scaffolding dimensions (2.8 m × 1.5 m) which allocates enough space to rotate and move the scaffold.

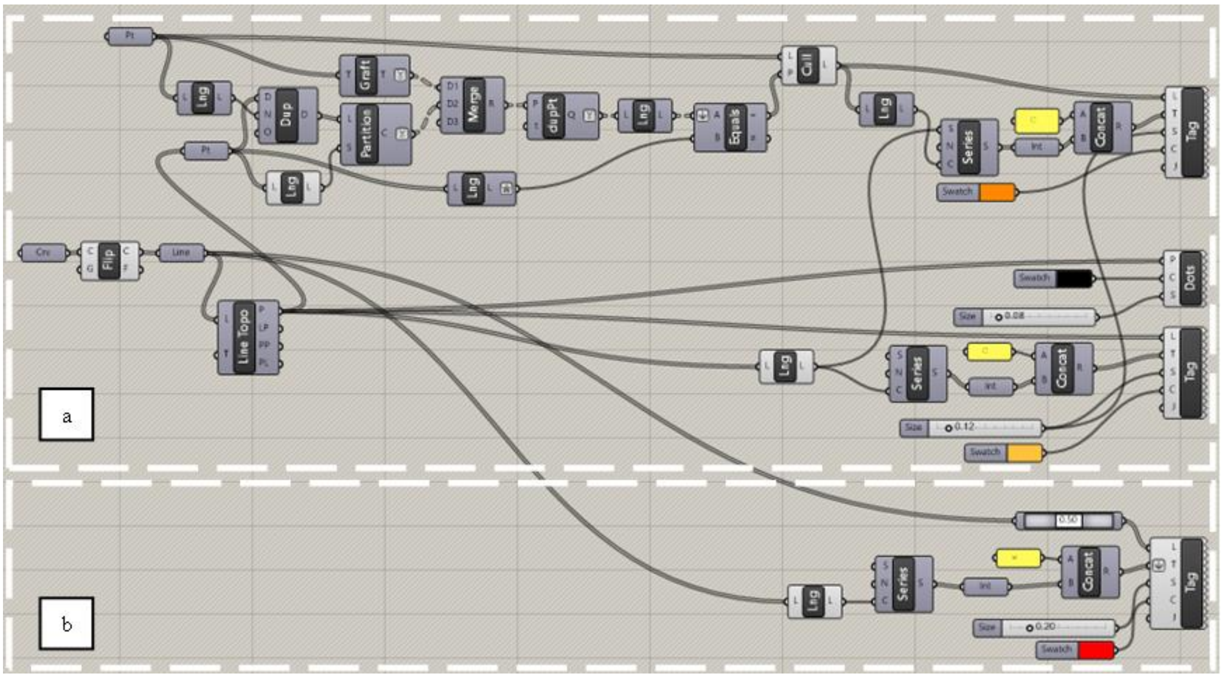


Figure 3: Automatic identification and enumeration of a)vertics, b)edges.

3.3 Step 3: Automate Workspace Taxonomy

The floor plan of the project was manually plotted as a graph in AutoCAD®. The edges in this graph represented the walls and the vertices represented the posts. Importing the graph into Rhinoceros 3D® software and using the Grasshopper® plugin, edges and vertices were automatically identified and numbered (Fig.3 and Fig.4). Rhinoceros 3D® is used since it is compatible with most CAD software and supports CAD file formats for importing. The main advantage of using Grasshopper® is that as a visual scripting language and parametric modeling add-on, it works along Rhinoceros 3D® and empowers the users to conduct quantitative analysis using visual programming as opposed to textual programming languages such as C# or Python, which require extensive coding.

The identified edges (walls) were classified into a limited number of categories (with a distance of 0.5m) according to their length (Fig.5). This categorization helps in three different ways. First, since walls in one category have the same workspace, allocating workspace could be conducted easier and faster. Second, predicting the frequency of visits to each module of the workspace could be done for each category once; therefore, the volume of calculations would be dramatically reduced. Third, it rounds up the time needed for constructing each element; therefore, linear arrays would be in integers. Regarding observations, the average construction time per meter of the wall was one hour fifty-one minutes, and thirteen seconds (1 unit of time). In this case, by classifying the walls and assuming that the construction time has a linear relationship with the wall length, the construction time of walls in each category could be determined.

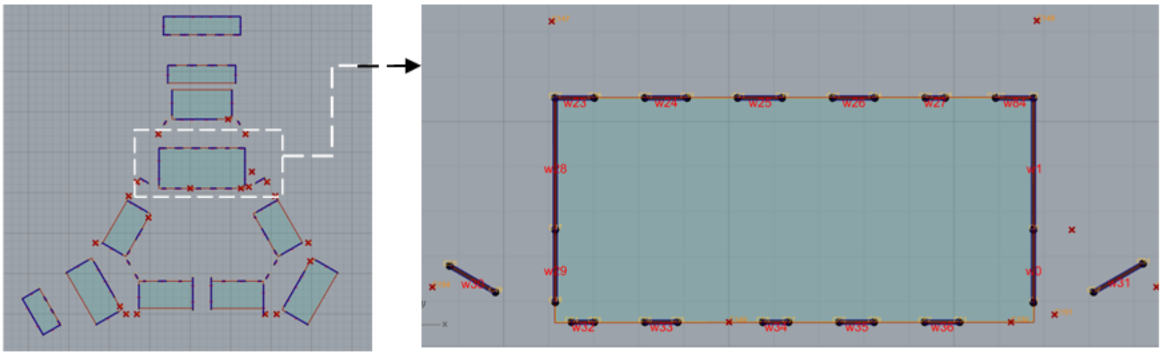


Figure 4: Graphical representation of enumerated edges and vertices in Rhino.

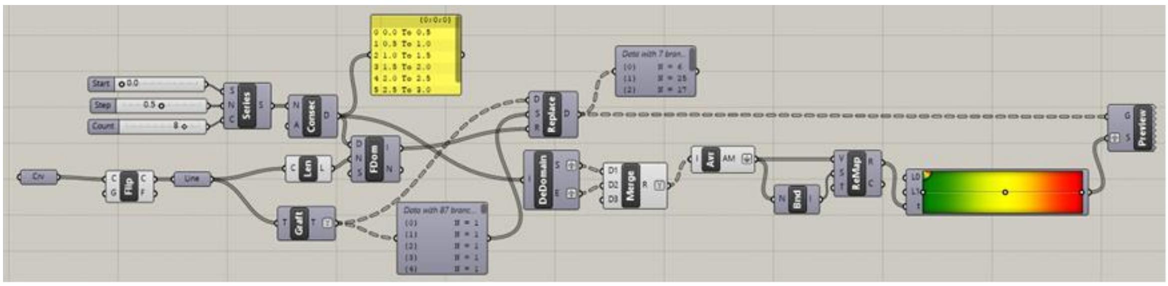


Figure 5: Automated blockwork activity workspace classification using grasshopper.

3.4 Step 4: Computing the Presence Probability Using Support Vector Machine Regression and Grasshopper ®

The risk of spatial-temporal clashes between concurrent activities is calculated by determining the probability of conflict between the workspace of each activity with other activities (in pairs) and the severity of the conflict. To determine the probability of conflict between two workspaces, in this study, we sought to find the probability of workers being present at any point of the workspace allocated to them for each activity. However, due to the lack of available information resources, the severity is assumed to be the same for different types of conflict (regardless of the construction method and activity type).

To predict the probability of workers being present at any point in the workspace, Support Vector Machine Regression (SVM) was used to anticipate the number of blockwork laborers' visits to each workspace module. Given a set of training examples that each belongs to one or two categories, the Support Vector Machine training algorithm creates a model that assigns new samples to a category and is, therefore, a non-probabilistic binary linear classifier. A Support Vector Machine model represents samples as points in space that are plotted in such a way that examples from separate categories can be distinguished from each other as much as possible. After being fitted, the model can be used to predict new values. It should be noted that using SVM regression in higher-dimensional spaces brings about computational complexity and requires more training time. Therefore, alternative machine learning methods like Random Forests or Gradient Boosting could be more suitable. To avoid overfitting or underfitting, careful tuning of hyperparameters such as the regularization parameter (C) and kernel parameters (e.g., gamma for RBF kernels) is needed.In this study, all SVM codes were produced with "scikit-learn" (Pedregosa et al., 2011), also known as Sklearn, an open-source machine learning library for Python programming language. The SVM codes were processed with Jupyter Notebook (Kluyver et al., 2016), an open-source browser-based computational environment.

The training examples for SVM were provided through observation (further details in 3.1). Being confronted with a Non-Linear Data Set and based on Cover's theorem (1965), a Radial basis function kernel (RBF) was used to map the input into high-dimensional feature spaces, making them more separable. To achieve nonlinear classification more accurately and in a more reasonable time, two parameters must be considered: C and Gamma. The parameter, which is called "C" in the Sklearn (Pedregosa et al., 2011) Python library, controls the margin hardness and trades off the misclassification of training examples against the simplicity of the decision surface. A low C makes the decision surface smooth, while a high C aims at classifying all training examples correctly. Gamma defines how much influence a single training example has (1.4. Support Vector Machines, n.d.). The higher the gamma value, the more the algorithm tries to perform the fit exactly on the basis of the training data set, which leads to an over-fitting problem. In this study, the C Parameter was set equal to 200, and Gamma was calculated based on the Sklearn module through the following formula:

Gamma= 1 / (Number of independent variables*Training data variance)

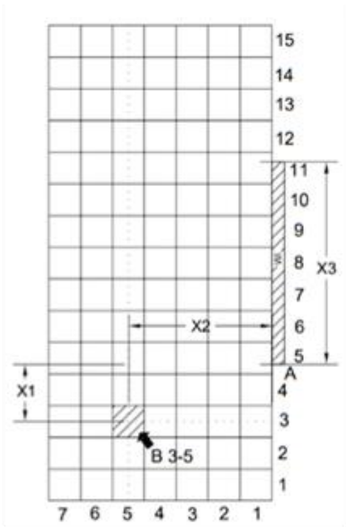


Figure 6: Independent variables in the regression: X1=distance from A, X2=Vartical distance from the wall, X3=distance between two wall-posts.

The number of workers' visits to each module (y) was considered to be a dependent variable, and the distance from A (X1), the vertical distance from the wall (X2), the distance between two wall-posts (X3), and the construction time measured in hours (X4) were considered to be independent variables. For each wall, point A was fixed and contracted. Thus, if the worker is standing in front of the wall in the center, point A is the post to his right (Fig. 6).

Of the 378 data observed, 10% (38) were randomly selected as test data, and fitting was performed on the remaining 340 data as training data. Table 2 shows the mean squared error in all data, training data, and test data, respectively.

Table 2: R2 score of conducted regression.

	R2 SCORE
All data	0.9589
Training data	0.9548
Test data	0.9573

Based on the regression, the number of blockwork laborer's visits to each module (x,y) during blockwork activity of the wall Wi (nC(x,y)Wi) for each category of walls could be predicted and stored. To anticipate the number of visits to each module (Y), the independent variable X3 (distance between two posts) was determined to be the maximum distance between two posts in that category. For example, in the category of the walls with the length between 1 and 1.5 meters, 1.5 was set as the independent variable X3. Furthermore, the execution time for blockwork activity was assumed to be a linear function of the length of the wall. In other words, it was assumed that as the length of the wall increases, the construction time increases at the same rate. After importing the predicted values of the number of blockwork laborer's visits to each module (x,y) into Grasshopper®, the probability of worker presence in each module for blockwork activity PC(x,y)Wi could be calculated as follows:

$$P_{C(x,y)wi} = \frac{n_{C(x,y)Wi}}{\sum_x \sum_y n_{C(x,y)Wi}}$$

Supplementary to this, the probability of post-installation workers' presence in each point of the required workspace was assumed to be the same, and the sum of them was set equal to one. Therefore, the probability of workers' presence in section i (Si) of the installation workspace of Post j (Pj) is PSiPj and could be calculated by the below formula where APj = total area of Pj workspace, and ASiPj = the area of Si in that workspace.

$$P_{SiPj} = \frac{A_{SiPj}}{A_{Pj}}$$

In order to consider the voids, if a portion of the workspace was located within the voids, the probability of workers being present in that area is zero and the reduced probability of presence would be proportionately added to the modules around the void so that the total probability of presence remains the same. In other words:

$$\alpha = \sum_x \sum_y n_{C(x,y)Wi} \times \frac{S_{V,C(x,y)}}{S_C}$$

$$n'_{C(x,y)} = \left(S_c - S_{V,C(x,y)}\right) \times n_{C(x,y)Wi} + \frac{(S_C - S_{V,C(x,y)})}{S_T - S_V} \times \alpha \; \forall x \in X, \forall y \in Y$$

$$P_{C(x,y)wi} = \frac{n'_{C(x,y)Wi}}{\sum_x \sum_y n_{C(x,y)Wi}}$$

In the above formula, ST = the total area of the workspace, SV = the total area located in the void, C(x,y)Wi = the module (x, y) for the wall Wi, SC = the area of the module (0.25 m2 in this study), SV,C = the area of modules located in the void, nC(x,y) = the number of visits to module (x,y) during blockwork activity of wall Wi, n'C (x,y) = the number of visits to module (x,y) after deducting the probability of being in the void, and PC(x,y)Wi = the probability of worker presence in module (x,y).

3.5 Step 5: Automated Workspace Visualization and Occupancy Grid Allocation

In this step, based on which category each edge of the graph (walls) belongs to, the workspace of each blockwork activity and the probabilities of worker presence associated with each module of the workspace (occupancy grid) are allocated using the Grasshopper plugin. It should be emphasized that due to wall thickness, the workspace allocated to each wall must be drawn with an offset of half of the thickness from the edge.

Correspondingly, the post-installation workspaces are automatically allocated, being a circle with an adjustable radius and center of vertices (based on step 2). The probability of worker presence in each section of these workspaces is calculated and modeled based on step 4 (3.4).

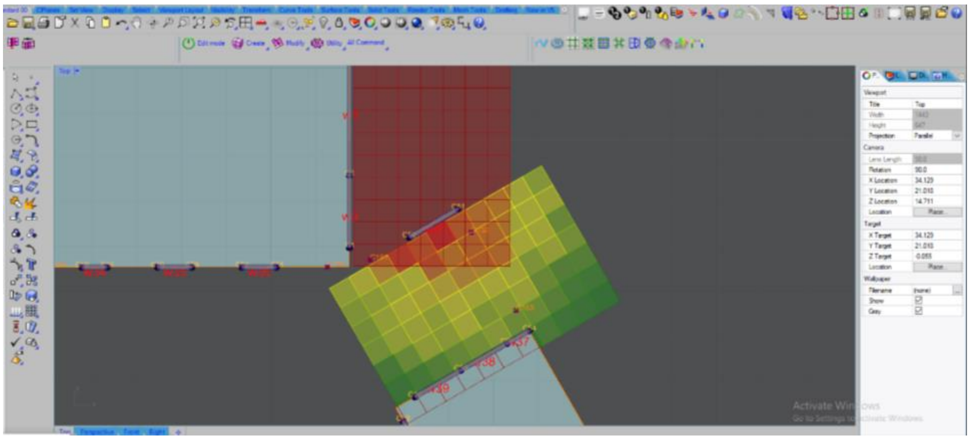


Figure 7: Automatic workspace conflict detection and safety score calculation: a) Graphical representation of Pair-wise blockwork - blockwork (w-w) conflict in Rhinoceros 3D®.

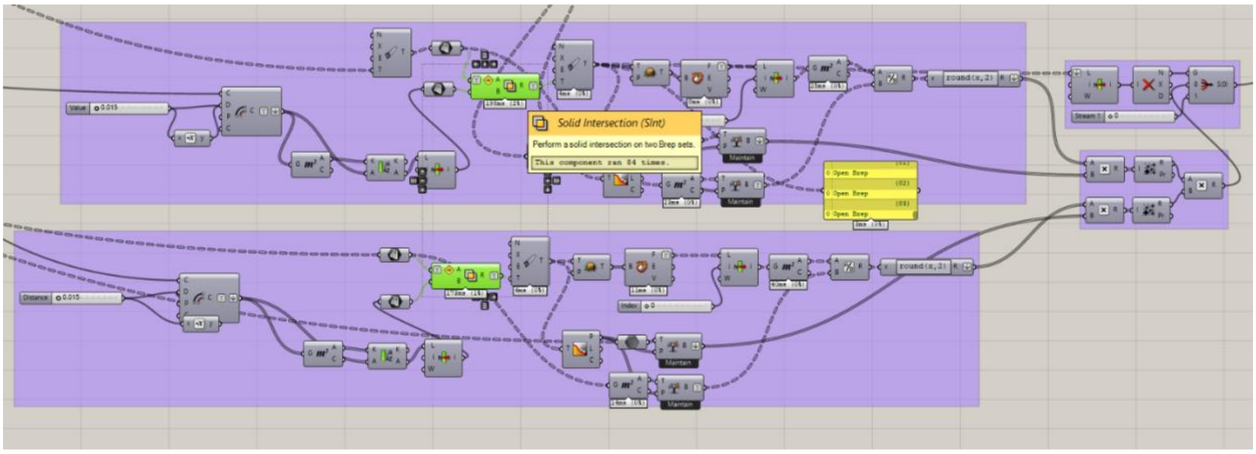


Figure 7: Automatic workspace conflict detection and safety score calculation: b) Automatic conflict risk calculation for blockwork - blockwork (w-w) activities using Grasshopper® components.

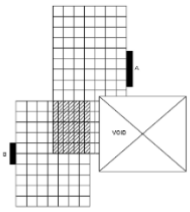
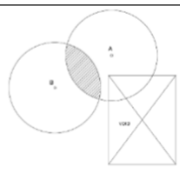
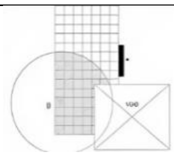
3.6 Step 6: Automatic pair-wise Conflict Risks Calculation

With the probability of workers' presence in each point of the workspaces, the risk of conflict between one workspace and others (in pairs) could be automatically calculated based on Table 3 using Grasshopper (Fig. 7). The safety score of conflict between workspaces indicates the risk of interference between them which is a number between zero and 1, and its lowest value occurs when two workspaces do not interfere with each other.

After computing the probability of workers' presence at each point of the workspaces (step 3.4), the risk of conflict between one workspace and others (in pairs) could be automatically calculated based on Table 3 using Grasshopper (Fig. 7). In other words, the safety score of conflict between workspaces indicates the risk of interference between them, which is a number between zero and 1, and its lowest value occurs when two workspaces do not interfere with each other. The importance coefficients in safety score calculation indicate the severity of each type of conflict, which could vary due to work environment characteristics (including working at height, adjacency to irregularly moving objects (e.g., a truck), safety measurement, and construction method) and human factors (including age, experience level, myopia, or illness). These factors could impact the severity of collisions between objects, workers, and vehicles and classify them into risks ranging from low-severe (including near-miss events and non-day lost cases) to high-severe incidents (including first aid cases, medical intervention, fatalities, and permanent incapacity). In this research, the significance of all three types of conflict (a- blockwork and blockwork, b- post-installation and blockwork, and c- post-installation and post-installation workspaces) was considered to be equal due to lack of information resources ($coef_{w-w} = coef_{p-w} = coef_{p-p} = 1$) . This limitation could be addressed in future studies by measuring the risk (calculated as assigned severity multiplied by probability) to provide a more reliable estimate.

For M (from 0-m) blockwork and N (from 0-n) post-installation workspaces, the Safety score of 3 types of conflicts could be calculated separately for a- blockwork and blockwork, b- post-installation and blockwork, and c- post-installation and post-installation workspaces, and stored as 3 matrices with dimensions of M*M, M*N and N*N respectively. In fact, the elements of these matrices represent the safety score of the interference of one workspace with another. These matrices are then saved to be used to evaluate the safety score of each construction schedule regarding each type of conflict.

Table 3: Calculation of safety score based on conflict type.

Conflict type	example	formula
Blockwork - blockwork (w-w)		Safety score = the probability of workers' presence in the overlapping area of workspace A × he probability of workers' presence in the overlapping area of workspace B × $coef_{w-w}$
Post installation- Post installation (p-p)		Safety score = the probability of workers' presence in the overlapping area of workspace A × he probability of workers' presence in the overlapping area of workspace B × $coef_{p-p}$
Post installation- blockwork (p-w)		Safety score = the probability of workers' presence in the overlapping area of workspace A × he probability of workers' presence in the overlapping area of workspace B × $coef_{p-w}$

3.7 Step 7: Work Sequence Conflict Detection and Scenario Safety Evaluation

For each schedule, the sequence of tasks by which each working crew must execute their job would be written by contractors as a linear array based on the enumerated edge and vertices. Hence, the number of arrays would be equal to the number of working groups. In these arrays, each element is representative of a unit of time. For example, The array [156, 156, -1,-1, 42,42, -1, -1, …, 12, 12, -1, -1] represent the working sequence of a working group that start their job with installing the post "156" for 2 units of time and waits for welding confirmation for the following 2 unit. After a lag of 2 unit of time, this working group resumes their job by installing the post "42". These arrays would be automatically cross-checked using python code to determine which activities are performed concurrently. The safety score obtained from the simultaneous execution of these activities would be read from the workspaces' interference matrices. Accordingly, the safety score of w-w, p-p, and p-w workspace conflicts, and ultimately the total safety score (Sum of the previous three) would be computed for each unit of time and the total construction time. These values could be used to evaluate different schedules in terms of spatial-temporal clashes and select a scenario with the least safety risk. Contractors also could be informed about the safety impacts of their work sequence.

4. CASE STUDY

To examine the technical feasibility of the proposed method, blockwork and post-installation activities were selected as the case study and were investigated in a large-scale hospital project ("Atieh 2") in Tehran. These activities could be executed simultaneously and have a mandatory dependency with each other. Thus, detecting work sequence conflicts between working groups of these activities and evaluating the safety of different construction scenarios in terms of the interference between workspaces of these activities is of much significance. Formerly, to avoid the risk of spatial-temporal clashes between the two activities in "Atieh 2" project, this risk was implicitly considered in the daily planning and the contractors were supposed to consider this risk when arranging their daily work sequence.

The 3D Model of the second floor of the "Atieh 2" was developed in BIM using Autodesk Revit® Structure software (Fig. 8-a). Among the 4 zone of the construction plan, zone A of this project was selected for extensive evaluation due to its activities' limited available workspaces, the presence of several voids, and the fact that as the core zone of the building the construction layout of this zone repeats in all floors (Fig. 8-b).

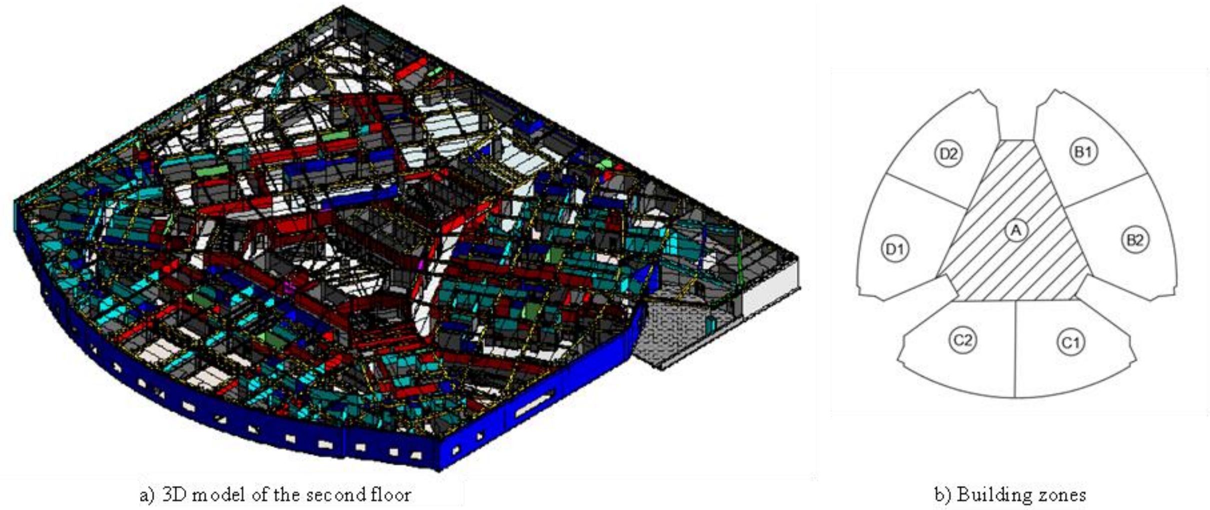


Figure 8: Case Study, Atieh 2 Building.

After plotting the construction layout as a graph in AutoCAD ®, the topological study was conducted on this graph in Grasshopper®. 87 edges (walls) and 164 vertices (posts) were automatically identified and enumerated. The identified edges were classified into 7 categories based on their length (Table 4).

Table 4: Classification of the identified edges (walls).

Category Number	Wall Length (m)	**Number of walls**	**Constriction time**
CAT 1	(0,0.5]	6	1
CAT 2	(0.5 ,1]	25	2
CAT 3	(1 ,1.5]	17	3
CAT 4	(1.5 ,2]	12	4
CAT 5	(2 ,2.5]	11	5
CAT 6	(2.5 ,3]	10	6
CAT 7	(3 ,3.5]	6	7

Using the empirical workspace parameters obtained from field observation, the required workspace for each activity was determined. Fig. 9 illustrates the results of the SVM regression conducted to determine the number of blockwork laborers visiting each module of their workspaces for each wall category (i.e., blockwork activity). Two key observations can be made: 1- As the wall length increases, the probability of blockwork laborers visiting each module also increases, as they require more construction time; and 2- The frequency of blockwork laborers' visits to modules decreases as the distance from the wall increases, eventually reaching zero at distances greater than 3 meters.The predicted values were then imported into Grasshopper® and used to automatically generate and allocate the 2D parametric occupancy grid of each construction element.

The safety scores of the interference of each workspace with other workspaces (in pairs) were calculated and separately stored for w-w, p-p, and p-w conflicts as 3 matrices with dimensions of 87*87, 164*164, and 164*87 respectively. Table 5 represents part of the calculated p-w interference matrix. For instance, the safety score of the conflict between blockwork of wall 84 and installation of post 2 was calculated to be 0.519556. These workspaces' interference matrices were imported into Jupyter Notebook as a .csv file to be used in scenarios' safety score calculation.

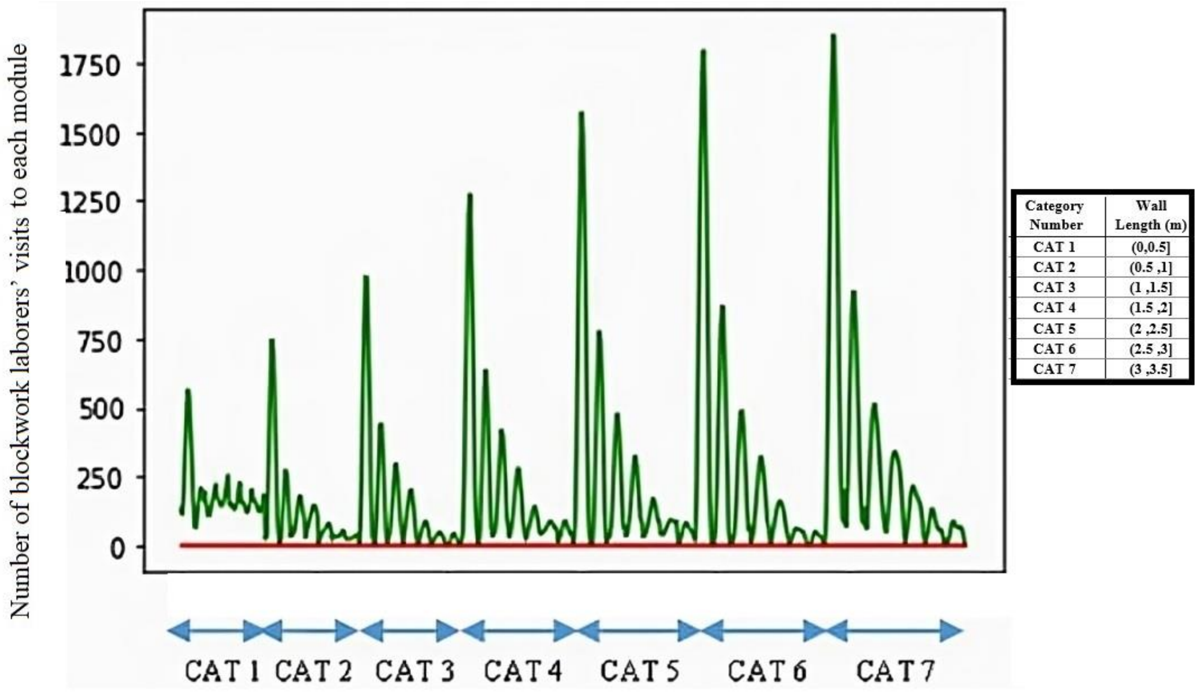


Figure 9: The prediction of the number of masonry workers' visit to each module of the allocated workspace.

Table 5: Part of p-w interference matrix.

	{0}	**{1}**	**{2}**	**{3}**	**{4}**	**...**	**{83}**	**{84}**	**{85}**	**{86}**
{0}	0.718338	0.639011	0	0	0		0	0	0	0
{1}	0.52383	0.153371	0	0	0		0	0	0	0
{2}	0.037754	0.430061	0	0	0		0	0.519556	0	0
{3}	0	0	0.530822	0	0		0.173033	0	0	0
{4}	0	0	0.493214	0	0		0.195739	0	0	0
⋮										
{161}	0	0	0	0	0		0	0	0	0
{162}	0	0	0	0	0		0	0	0	0
{163}	0	0	0	0	0		0	0	0	0
{164}	0	0	0	0	0		0	0	0	0

It is practically not plausible to investigate all possible scenarios for executing 164 post-installation and 84 blockwork tasks which doing so requires optimization methods and was not within the scope of this research. Therefore, 5 detailed compressed scenarios were developed in which the blockwork and post-installation activities in Zone A of the case study were executed simultaneously. In these scenarios, the sequence of activities and the duration of activities were taken into consideration. The quantity of labor for each type of activity was determined to be equal to 2 regardless of the construction element type or the required construction time, as it was conventional in this project. Based on the gathered data from the field observation, the installation time of each post was determined to be 2 units. Moreover, the construction time for each wall was considered to be a linear function of the length, 1 unit per 0.5 m. Bearing the precedence relationship between activities in mind, all scenarios were scheduled in a way so that working crews are constantly available, and no crew will be kept idle while an activity is waiting to be executed. Furthermore, all activities were planned to be executed on their Early Start (ES). Ultimately, the total construction time was estimated for each construction scenario.

For each schedule, the work sequence of each working crew (3 groups of blockwork laborers and 2 groups of post installers in this study) was specified. However, the number of working crews, and correspondingly the number of work sequences, is considered to be adjustable in the method. Work sequences of each schedule were automatically cross-checked using python code to identify simultaneous activity execution in each unit of time which specifies the safety score of each schedule in terms of different types of conflicts (w-w, p-p, and p-w) and the total safety score. The safety score computation was done based on the imported workspaces' interference matrices. The schedules were then compared in terms of safety performance to select the safest construction scenario. In this case "safest" refers to the minimal conflict between allocated workspaces. The calculation results for the safety score of the different scenarios are listed in Table 6 regarding different types of conflict. The results indicate that the first scenario had by far the least total safety score expected in the site in comparison with those of other scenarios and had to be opted as the safest schedule. This scenario also was responsible for the least p-p and p-w conflicts. In all scenarios, the collision between post-installation's and blockworks' workspaces accounted for the lion's share of the total safety score. This fact highlights the importance of this type of conflict and necessitates proportionate safety measures. However, it should be pointed out that the importance coefficient and severity of risks were assumed to be the same for all three types of conflict. If different coefficients were considered for each type of collision, the final result would vary and this could be considered as a topic for future research.

Table 6: Safety score computation results for scenarios.

Scenario	Safety score of w-w conflict	Safety score of p-w conflict	Safety score of p-p conflict	Total safety score	Construction time
1	5.031964	34.78495	0.901578	40.71849	330
2	4.296698	39.95911	1.347438	45.60324	330
3	12.52582	42.696109	2.99719	58.22182	331
4	11.73897	40.360568	3.468897	55.56844	335
5	10.38231	42.002659	5.09599	57.48096	334

Comparing safety scores of different schedules determines the level of safety (in terms of the risk of spatial-temporal clashes between activities) expected in the site in each scenario and could equip project and construction managers with the required knowledge to make informed decisions regarding work sequences. Fig. 10 depicts the total safety score results for different scenarios in each unit of time.

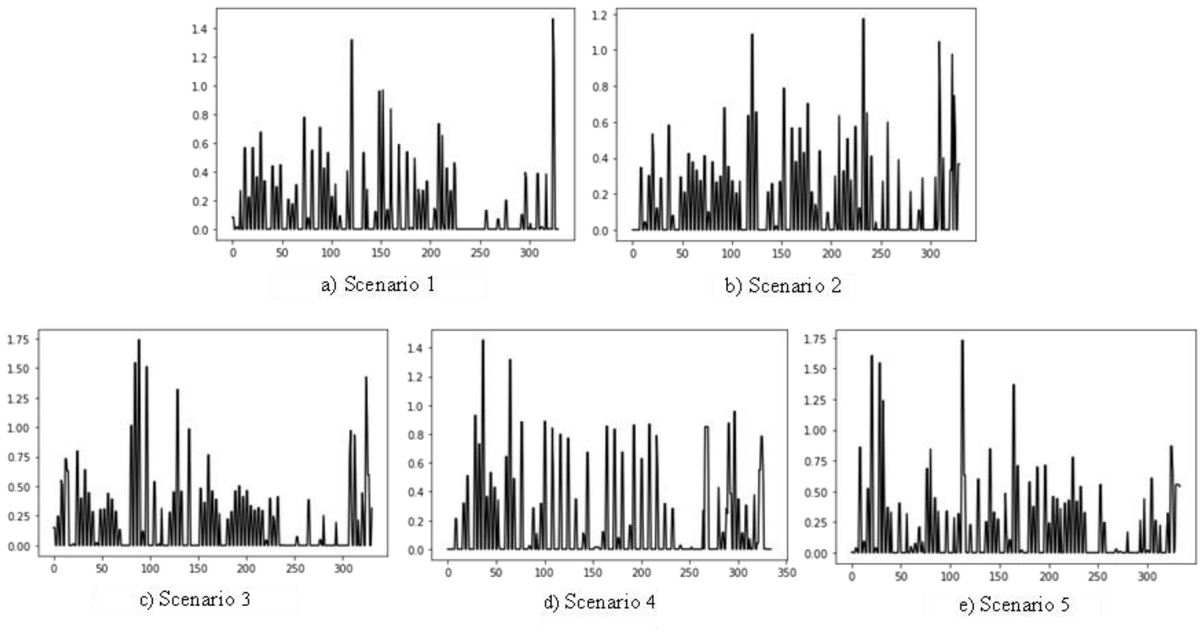


Figure 10: The total safety score results for different scenarios in each time unit.

Similar charts could be produced showing the safety scores of different scenarios concerning each type of conflict in each unit of time and cumulatively. For example, Fig. 11 represents the safety score of different types of conflict in each unit of time in the first scenario.

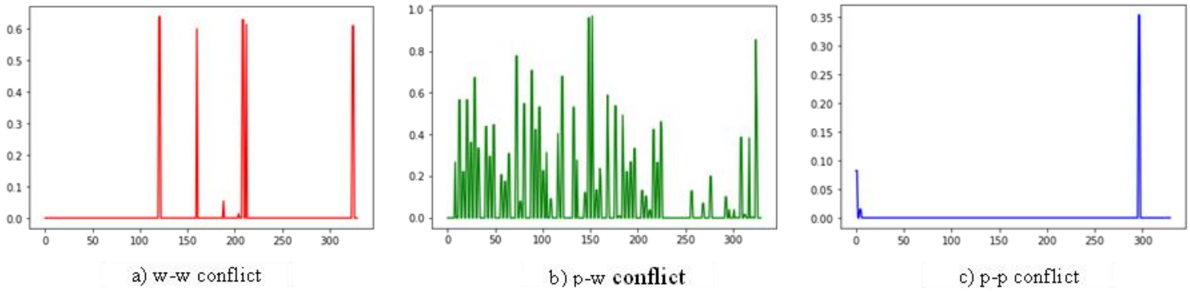


Figure 11: Safety score of different types of conflict in each time uint in scenario 1.

One application of the developed prototype is that using these charts high-risk work periods could be identified in any schedule, thus, workers can be warned, and safety personnel could plan safety measures in advance. For instance, as shown in Fig. 10, the highest total safety score of 1.7329 occurs in unit time 112 in scenario 5, which includes all the w-w, p-w, and p-p conflicts. Supplementary to this, a threshold (e.g., a safety score of 1.5) could be determined by which periods with a safety score higher than this value could be identified and be used to alert safety personnel or to oblige the amendment of work sequences. In scenario 5, excluding unit time 112, this threshold exceeds in time units 21 and 29 with safety scores of 1.6045 and 1.5438, respectively.

5. DISCUSSION

This paper presents an automated procedure for detecting and scoring spatial-temporal conflicts in limited construction sites. This method receives and processes activity-specific workspace information to automatically classify, generate, and allocate the workspaces in BIM. The proposed method takes into account the activity-specific geometric parameters, and the probability of workers' presence in allocated workspaces (predicted by SVM regression) to conduct automatic pair-wise conflict risks calculation. The pair-wise conflict risks calculation output is safety score matrices discussed in section 3.6. Based on the safety score matrices, which concern different types of conflicts (w-w, p-p, and p-w), conflict detection in each scenario is carried out through automatic cross-checking of the working group's work sequence using python code. Subsequently, the safety scores of each scenario are calculated for each unit of time and cumulatively.

The calculated safety scores are numbers between 0 and 1, zero indicates there is no conflict between workspaces. Decision-makers could primarily use the safety scores as the criteria to compare different construction scenarios and select the most appropriate option based on the risk of spatial-temporal conflicts between activities' workspaces. The safety scores can also be used to determine high-risk periods. Identifying high-risk periods could alert safety personnel to take the necessary measures to proactively respond to risks and notify them about the level of safety expected at the site at different times.

The presented BIM-based method is superior to traditional heuristic approaches of conflict detection and analysis, since: 1- The processes of workspace generation, classification, allocation, and conflict detection are automated, 2- Instead of relying on expert opinion to detect conflicts based on 2D layouts, which is error-prone, work sequences are automatically cross-checked, which ensures that no conflict has been missed and the dependence on humans is reduced. 3- The dynamic nature of construction and spatial and temporal information of activities are considered during the hazard identification process, and conflict risks are calculated for each unit of time. 4- If changes happen in the process, recalculating the safety risks is much easier than the conventional methods, 5- Safety planning is integrated into the planning phase, and hazards could be identified prior to construction. 6- The overall safety communication is enhanced as all the teams could be informed about the safety impacts of their work sequence in advance and make adjustments if it is required by the project planner or the safety manager.

Another novelty of the developed method compared to other previously developed automated conflict detection methods and commercially available 4D Virtual Construction Scheduling and Simulation software such as Autodesk® Navisworks® and Synchro Pro is that; 1-it avoids unrealistic conflict detection, and 2- it quantifies the risk of spatial-temporal conflicts. Since laborers occupy only a portion of the activity workspace during each time interval (Mirzaei et al., 2018), the present method considers the dynamic evolution of activities' workspaces during the workspace generation to avoid the unrealistic conflict detection. In other words, instead of using Bounding Box variants to represent workspaces (adopted by Chavada et al., 2012; Moon et al., 2014a; Kim & Teizer, 2014; Kim et al., 2016; Mirzaei et al., 2018; Dashti et al., 2021; Wang et al., 2019), the workspace usage is represented by allocating occupancy grids to each construction element (in the case study: walls and posts). Although software applications as an add-on for Autodesk® Navisworks® Manage (Dashti et al., 2021) or BIM-based approaches (Zhang et al., 2015b) have been developed to compute workspace collision in existing literature, their if-then rules were based on expert opinion or historical data. In the proposed method, the occupancy grids are parametrically generated in Grasshopper® based on SVM regression for blockworks' workspaces and observation for post-installation workspaces and represent the probability of workers' presence at any point in the allocated workspaces.

The two activities investigated in this study (blockwork and post-installation) were not specifically present in the body of literature. Therefore, the activity-specific information, including the required workspaces and the extent to which workers use the allocated spaces, was not available. In this study, an attempt was made to fill this gap by collecting this information through field observation and processing it through SVM regression. The findings and the results can be used by other researchers to validate their automated safety or planning frameworks in the future. In this study, the process of extracting activity-specific workspace data is done by recording videos, converting the videos into photos with two-second intervals, and manually examining the photos to enter the data (number of blockwork laborers' visits to each module of the workspace). The extracting activity-specific workspace parameters could be done by developing a GIS-based technology to make this process simpler by sacrificing accuracy. GIS-based techniques can provide raw data for the SVM algorithm, developed in this study, to create a dataset of the workspace and presence probability for different construction activities.

The number of working groups, the size of the workspaces, the frequency of workers' visits to each point of the allocated workspace, and the execution time of each activity were considered to be adjustable. Therefore, all the codes in this research, including the pair-wise conflict risks calculation in Grasshopper® and the scenario evaluation code in Python could be generalized to examine other activities.

Since the main focus of this study was on conflict probability, the severities of conflicts were assumed equal. This limitation could be addressed in future studies. Secondly, evaluating all possible scenarios requires optimization algorithms that were not within the scope of the present study. However, this research has the potential to lay the groundwork for additional investigation into the optimization. Novel algorithms could be developed to use the calculated safety score and other criteria, namely time and productivity to optimize the work sequences.

Finally, this method has the potential to serve as a tool for measuring social distancing during a pandemic like COVID-19. The practical application of the proposed method during a pandemic (e.g., COVID-19) and periods of similar contagious viruses could be investigated in future studies, inasmuch as it has the potential to empower site managers and project planners with the ability to integrate social distancing into the workspace management, particularly in the case of large-scale projects. Such an outcome could be achieved by using this method to parametrically generate workspaces regarding official guidance or protocols (e.g., at least 6 feet according to the OSHA COVID-19 Guidance) and evaluate work sequences in terms of workspaces' spatial-temporal conflicts. Consequently, project managers could request contractors to alter work sequences to ensure they meet social distancing requirements and select the construction scenario with the least health-related hazards.

6. CONCLUSION

This paper presented a novel method that evaluates work sequences in terms of the risk of spatial-temporal conflicts between simultaneous activities in construction sites. The method consists of five components; construction workspaces 2D graph, BIM model, Support Vector Machine regression, safety score matrices, and scenario evaluation code in Python.

The spatial requirements of construction activities in this study are based on the empirical data collected. This data is used for workspace generation and allocation processes. Pair-wise conflict detection and analysis are conducted to form the safety score matrices for different types of conflicts. These matrices are used as the inputs for scenario evaluation code in Python. Compared to previously developed automated conflict detection methods (e.g., using variants of the Bounding Box idea), dynamic evolution of activities' workspaces was taken into consideration, which results in avoiding unrealistic conflict detection.

The case study results demonstrate the applicability of the proposed method in evaluating different construction scenarios and selecting the safest one (concerning the safety impacts of concurrent activities), identifying high-risk periods, and determining the level of safety expected in construction sites in each scenario. The findings help the safety managers proactively respond to risks and the construction planners to select the construction scenario wisely. All spatial-temporal parameters (e.g., the number of working groups, the size of the workspaces, the frequency of visits to each point of the allocated workspace) were considered to be adjustable. Although employing the proposed method on large-scale projects with innumerable concurrent tasks could bring about computational complexity, the pairwise conflict risks calculation in Grasshopper® and the scenario evaluation code in Python have the potential to be generalized to examine other activities. To facilitate the process, GIS-based technology could be used to extract activity-specific workspace parameters with less accuracy. Moreover, machine learning algorithms with faster training times and less computational cost, such as Random Forests or Gradient Boosting could be used for larger datasets, and novel algorithms could be developed to optimize work sequences based on the severities of conflicts, time, and productivity. Recognizing the limitation of uniform conflict severity, future research can focus on assigning variable weights to different conflict types, while being mindful of the potential increase in computational complexity. Recognizing the limitation of uniform conflict severity, future research can focus on assigning variable weights to different conflict types, while being mindful of the potential increase in computational complexity.

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